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An analysis of the feasibility of an extreme operational risk pool for banks

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Abstract

Operational risk events in banks include extreme events with significant losses being incurred and with substantial impact on share prices. A pooling arrangement between banks that would be able to reduce overall costs and reduce share price impacts would seem desirable, but one of the major inhibiting factors to establish the feasibility of such a pooling arrangement is that statistical models of these extreme events are difficult to build with any reliability. This paper uses both quantitative and qualitative analysis of operational risk losses for EU and US banks over the period 2008–2014 to establish the feasibility of creating a pooling arrangement between the banks and concludes that such an arrangement might be feasible but would require compulsory membership of the pool and capping of losses.

Keywords

Extreme operational risk losses; Pooling of losses; Insurance of extreme events

JEL Classification

G21; G22

1. Introduction

Li *et al*. (2017) analysed extreme operational risk events in US and EU banks from 2008 to 2014[1] based on data provided by ORIC International, where an extreme event was one where the recorded loss was greater than $US100 million. The number and amount of the extreme operational risk losses determined by Li *et al*. (2017) are summarised in Table 1.

Over the period 2008–2014, US banks incurred almost $700 billion losses from extreme operational risk events, and EU banks incurred almost $200 billion losses. In terms of relative impact, losses over $1 billion clearly have the greatest impact on profits and extreme operational risk losses in banks

[1] ORIC International, https://www.oricinternational.com

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Table 1. Extreme operational risk losses.

	Number of events		Losses	($US million)
Losses	US	EU	US	EU
> $1 billion	40	25	$654,147	$183,812
$500 million–$1 billion	64	11	$14,491	$7,515
$100–$500 million	23	24	$13,407	$5,590
Total	127	60	$682,045	$196,917

appear highly skewed which is consistent with the results in Ganegoda & Evans (2013). Just to put these losses into perspective, the total assets of US and EU banks at the end of 2014 were $US 16 trillion[2] and $US 23 trillion[3], respectively, spread across 5,573 US banks and 3,972 EU banking groups. Whilst the number of banks incurring the extreme operational risk events is then relatively small and the impact on the banks' asset bases is moderate, there is a much greater impact on the share price and hence the reputation of the offending banks. Sturm (2013) considered the impact on German banks' share price of announcements of operational losses and concluded that there was evidence of negative cumulative abnormal returns following both the announcement of the operational loss and the announcement of the settlement. Similarly, Fiordelisi *et al.* (2014) concluded from a study of operational risk losses in US and EU banks between 1994 and 2008 that there was substantial reputational damage following the announcement of the losses. Given the likely disproportionate impact on each bank when an extreme operational risk event occurs, it may well be in the interests of banks to develop a pooling or insurance arrangement for these larger losses to reduce the impact on share price of the individual bank. Such a pooling arrangement may well be of interest to regulators as significant reputational damage to a bank may affect the stability of the banking system. In this paper, we will only consider the feasibility of an inter-bank pooling arrangement, but we recognise that insurers may well be able to offer insurance even if an inter-bank pooling arrangement were not feasible if they have other uncorrelated insured risks. This paper is concerned only with the actuarial issues around the feasibility of an extreme operational risk pooling arrangement and not with the other issues such as regulatory and political feasibility.

2. Sustainable Pooling Issues

The main actuarial criteria for a sustainable pooling arrangement for extreme operational risk events is that the expected frequency and severity of claims must be reasonably predictable within acceptable bounds. To achieve this the pool needs a sufficiently large number of participants with identifiable and bounded potential losses and where the different risks are priced appropriately. In addition, the feasibility of the pooled arrangement would be greatly enhanced if there could be shown there was a low expected correlation of events across the banks, as this would allow a pricing structure that would be advantageous to participating banks as their contribution to the pool would be less than the losses potentially incurred by themselves. The pooled arrangement would then allow a spreading of costs across banks and across time. In this paper, given the low frequency of observed extreme operational risk events, and the actuarial importance of the correlation of extreme

[2] https://ycharts.com/indicators/us_banks_total_assets

[3] European Central Bank, https://www.ecb.europa.eu/press/pr/date/2015/html/pr150828.en.html and X-RATES http://www.x-rates.com/average/?from=USD&to=EUR&amount=1&year=2014

operational risk events to the feasibility of the pool concept, we will use two approaches to analyse the historical occurrence of extreme operational risk events:

- First, we will determine the Pearson coefficient for losses versus year of occurrence and bank name versus year of occurrence to determine statistically the independence of the extreme operational risk events. As the number of events being considered is relatively small, we will also observe the number of banks with single-year events and multiple-year events as a proxy for the frequency of events and observe for those with single events, the distribution of the events across the years as a proxy for correlation.
- Second, given the relatively small number of extreme operational risk events that can be quantitatively assessed with any reliability for determining future occurrences, we will use a qualitative assessment and consider the underlying characteristics of the historical extreme operational risk events to determine the drivers of the events as a means of understanding the commonality of the drivers and hence the likely correlation of future events.

3. Empirical Analysis

Table 2 shows the Pearson Coefficient for US and EU extreme operational risk losses against the year of loss, and also the year of loss against the bank name which was determined by giving each bank a unique numerical code.

The Pearson coefficient indicates there is no significant correlation between losses and years, nor between years and banks, indicating that for the period analysed, losses are reasonably independent within the constraints of the measure used and the relatively small data used. To test the reliability of the Pearson coefficients, the data were categorised into three periods, 2008–2010, 2011–2012 and 2013–2014. Tables 3 and 4 show the distribution of the number of banks incurring multiple period losses, and the average loss.

We have also analysed the distribution of single events across the three periods in Tables 5 and 6.

The results in Tables 3–6 empirically support the implication of the Pearson coefficient and indicate that during the period 2008–2014, around 75% of banks in the United States and the European with

Table 2. Pearson coefficient.

	Year versus loss	Year versus bank
US	0.011	− 0.254
EU	− 0.144	−0.044

Table 3. US banks, distribution of multiple events.

Number of periods of losses	Total losses ($US billion)	Percentage of banks	Average loss per bank ($US billion)
1	$513	77	$12
2	$20	13	$3
3	$97	10	$16

Table 4. EU banks, distribution of multiple events.

Number of periods of losses	Total losses ($US billion)	Percentage of banks	Average loss per bank ($US billion)
1	$42	75	$2
2	$103	25	$13
3	$0	0	$0

Table 5. US banks, distribution of single events.

Period of loss	Number of banks	Total losses ($US billion)
2008–2010	7	$3
2011–2012	15	$477
2013–2014	20	$22

Table 6. EU banks, distribution of single events.

Period of loss	Number of banks	Total losses ($US billion)
2008–2010	3	$3
2011–2012	10	$21
2013–2014	10	$14

extreme operational risk losses had a loss in only 1 period, i.e., most of the banks are not "serial offenders". In the United States, most of the losses by value have occurred in banks with losses in only one period, but this pattern is not observed in the European where those banks with events in two periods have the most losses by value[4]. The US banks with events in all three periods have larger average losses than the other US banks and in the EU banks, those with events in two periods have higher average losses than those banks with only one event. Overall, this analysis suggests that the distribution of losses is heavy tailed with a few banks having both a higher frequency of events and a higher severity of losses. The results in Tables 5 and 6 indicate that by number of banks, there has been a reasonably even distribution of events across the different periods, but the distribution by value of the losses is highly concentrated.

4. Qualitative Analysis

Financial markets, and financial institutions exhibit the features of a complex adaptive system which do not lend themselves to statistical modelling (Daníelsson, 2008). Further, Mittnik *et al.* (2013) counselled against placing too much reliability on both Pearson coefficients and copulas when analysing operational risk co-variability. To give greater breadth and depth to the analysis of the feasibility of a pooled arrangement for sharing extreme operational risk losses across banks, particularly given the relatively small amount of data and the skewness of the extreme operational risk losses, we have determined the drivers of the extreme operational risk events, using a process known

[4] We have cleaned the data so that losses from an event are only recorded once, thus eliminating as far as possible "double counting" of some events.

as cladistics analysis. This analysis tests for systemic drivers that would suggest high correlation of extreme operational risk events. Cladistics analysis was originally developed to assist biologists to estimate the likely evolutionary path of animals based on their characteristics, but it has recently been more widely used to understand how organisations work (Mitleton-Kelly, 2003), and how cultural inheritance in social systems occurs (Matthews *et al*., 2013). In the financial field, cladistics analysis has been used to study the drivers of significant derivative events (Allan & Corrigan, 2013), operational risks in banks (Li *et al*., 2017) and the World Economic Forum 2014 risks (Evans *et al*., 2017). Cladistics analysis produces a hierarchical structure of the characteristics starting from the characteristic that is unique to an event and moving through the characteristics that are common to several events until it determines the characteristic common to the most events that is possible. To construct cladistics trees, we used the maximum parsimony method, which is based on the theorem of Occam's razor which states that assumptions for explaining phenomenon should be as few as possible so as to construct the tree that minimises the number of steps required to generate the variation in the sequences from the common ancestor. Defining the difference between two sequences with length $L, u = (u_1, \ldots, u_L)$ and $v = (v_1, \ldots, v_n)$, then the non-normalised Hamming distance:

$$diff(u, v) = |\{k \mid u_k \neq v_k\}|$$

and given sequences A of length L, with a corresponding tree T, the Parsimony Score is

$$\mathrm{PS}(T, A) = \min_{\lambda} \sum_{\{u,v\} \in E} diff(u, v)$$

Where the minimum is taken over all possible labels λ of the internal nodes of tree T.

To find the most parsimonious tree, denote the value of the character for node v by $c(v)$, and for each leaf v:

$$S(v) = c(v)$$

For inner node v with "children" u, w:

$$S(v) = \begin{cases} S(u) \cap S(w), & S(u) \cap S(w) \neq \phi \\ S(u) \cup S(w), & S(u) \cup S(w) = \phi \end{cases}$$

If $S(u) \cup S(w) = \phi$, the parsimony score will be incremented by 1. By enumerating all possible trees, the one with minimum Parsimony Score is the most parsimonious tree. The output of a cladistics analysis is typically a tree structure that makes it easy to see the linkages that are estimated to have occurred. Figure 1 shows a simple illustrative cladistics tree for a series of events E1–E8, and their characteristics C1–C11. In this simple system, Event 1 has characteristics C1, C2 and C4 and shares C2 with Events 2 and 3, and C1 with Events 2, 3, 4 and 5. C1 and C9 can be regarded as the most systemic characteristics, i.e., they are the most common characteristics, whilst C4, C5, C6 and C8 are the least systemic. Real systems usually are a lot more complex than shown in Figure 1 with several branches between the systemic and least systemic or unique characteristics. Characteristics C1 and C9 can be thought of as the "Tier 1" characteristics, and C2, C3, C7, C10 and C11 as the "Tier 2" characteristics. In an analysis of financial systems, the input is a list of events with their characteristics derived from descriptions of the events either simply from observation or analysis of the common words used in the description of the event, with the consistency index used to give comfort that the characteristics chosen give a consistent output.

We have used cladistics analysis to determine the systemic drivers of the US and EU extreme operational risk events over the period 2008–2014. A high degree of commonality and sustainability of the systemic drivers of the extreme operational risk events across banks and across geographic

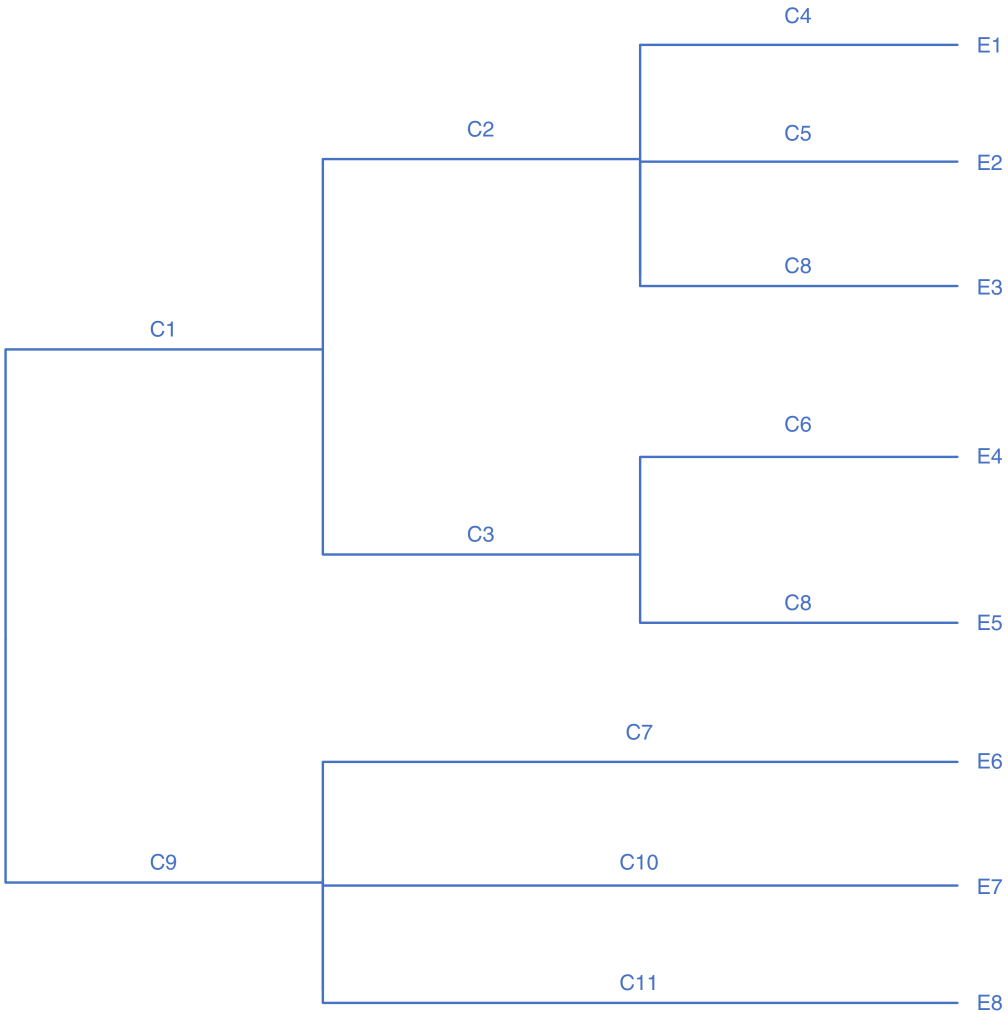

Figure 1. A typical cladistics tree.

zones would be indicative that in the longer term, banks may well have similar events with a high correlation of losses as the events are driven by common characteristics. The cladistic trees for US and EU extreme operational risk losses over the period 2008–2014 are shown in Appendix A for the more significant groups[5]. A sample "tree" for the "US poor controls group" is shown in Figure 2.

The most systemic characteristics, i.e., those on the left side of the trees are summarised in Table 7.

The results in Table 7 indicate that there is significant commonality in the systemic characteristics of the extreme operational risk events across the US and the EU banks. Furthermore, the number of systemic characteristics is reasonably small, indicating a significant commonality in the major drivers of extreme risk events. This result is consistent with the findings of Chernobai *et al.* (2011) who

[5] The full cladistics trees are available from the corresponding author.

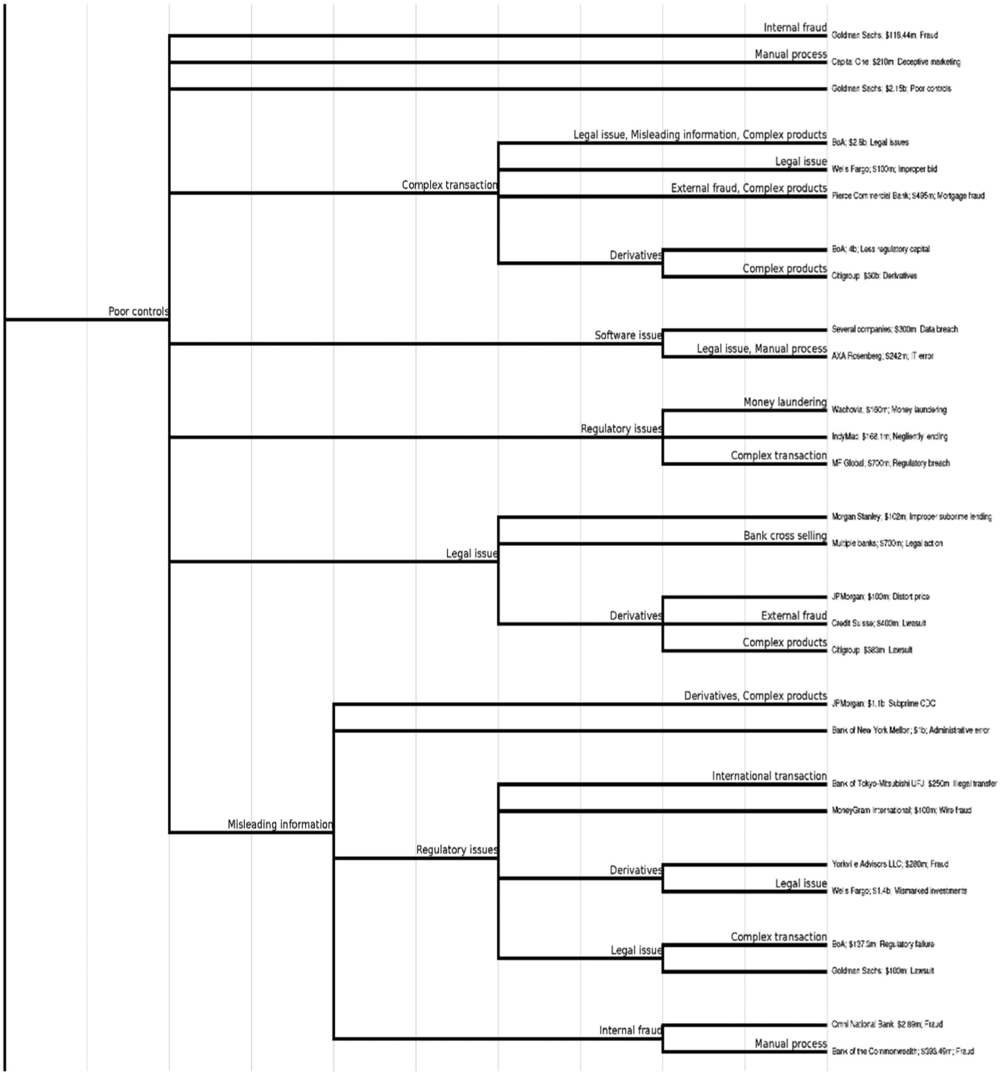

Figure 2. US poor controls group.

Table 7. Systemic characteristics 2008–2014.

US	EU
Internal fraud	
Legal issue	Legal issue
Misleading information	Misleading information
Poor controls	Poor controls
Regulatory issue	Regulatory issue
	Software issue

Source: Li *et al*. (2017).

found what we have called poor controls was also a significant driver of operational risk events but our study questions the assumption Chernobai *et al.* (2011) made of independence of operational risk events, and also questions the reliability of quantitative analysis, such as the Pearson coefficient when analysing extreme events in a complex adaptive system. The cladistics analysis has a similar objective to that of Chavez-Demoulin *et al.* (2016) who analysed covariates of causes of operational risk events, but our analysis uses a different approach and importantly, does not make any assumption as to independence of the risk events and has shown there is significant dependence in terms of the systemic characteristics of extreme operational risk events.

5. Network Analysis

Cladistics analysis identifies the systemic characteristics of risk events, but a closer observation of the trees in Appendix A will show that the systemic characteristic for a particular group of events also occurs in other groups of events at lower levels of systemic importance. It is difficult to easily identify the overall extent of the influence of some characteristics from the cladistics analysis where the characteristics occur in several groups of events. Network analysis is concerned with the totality of the influence of characteristics on the risk events and compliments the cladistics analysis. Network analysis of the financial system is gaining attention with recent papers including Haldane & May (2011) who looked at the systemic risk in the banking system resulting from interconnectedness, Battiston *et al.* (2016) who argued economic policy needs interdisciplinary network analysis and behavioural modelling and Joseph & Chen (2014) who looked at interconnectedness indicators as predictors of potential financial crises. We will use network analysis to indicate the overall degree of importance in the network of the characteristics of extreme operational risk losses. Based on Bavelas (1950) and Leavitt (1951) and the features of the network, we have used eigenvector centrality as the measure of importance of the characteristics. Figures 3 and 4 set out the network diagrams for the US and EU extreme operational risk events and their characteristics with the major connectivity[6]. The red dots are the extreme operational risk events and the blue squares are the dominant characteristics that are linked to the risk events. The more graphically central the characteristic, the more events are connected to it.

The dominant characteristics from Figures 3 and 4 are summarised in Table 8 in descending order of degrees of connectivity which measures the number of risk events connected to each characteristic.

The results in Tables 7 and 8 indicate that there is not much difference between the dominant characteristics determined by the cladistics analysis and the network analysis, but the network analysis has found that there are more common characteristics between the US and EU banks than appears from the cladistics analysis. The combined result is indicative of there being significant commonality of the systemic characteristics of extreme operational risk events across the United States and the European, but the network analysis indicates there is a reasonable range of causes of the extreme operational risk events.

6. Feasibility of an Extreme Operational Risk Pool

In order for a pooled arrangement for sharing extreme operational risk losses across banks to be actuarially sustainable, it is necessary that there are a large number of participants, the expected

[6] The full network diagrams are available from the corresponding author.

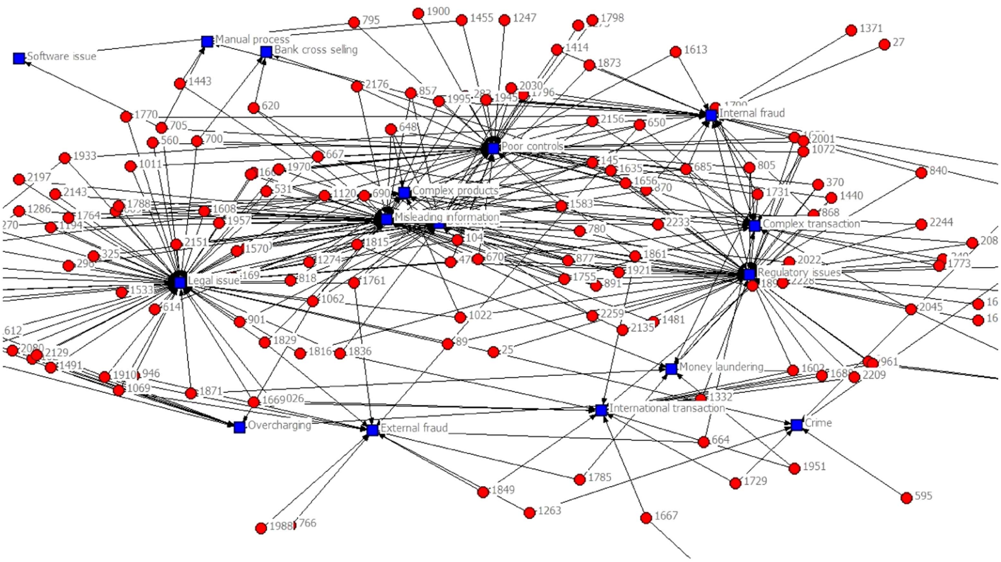

Figure 3. US major connections.

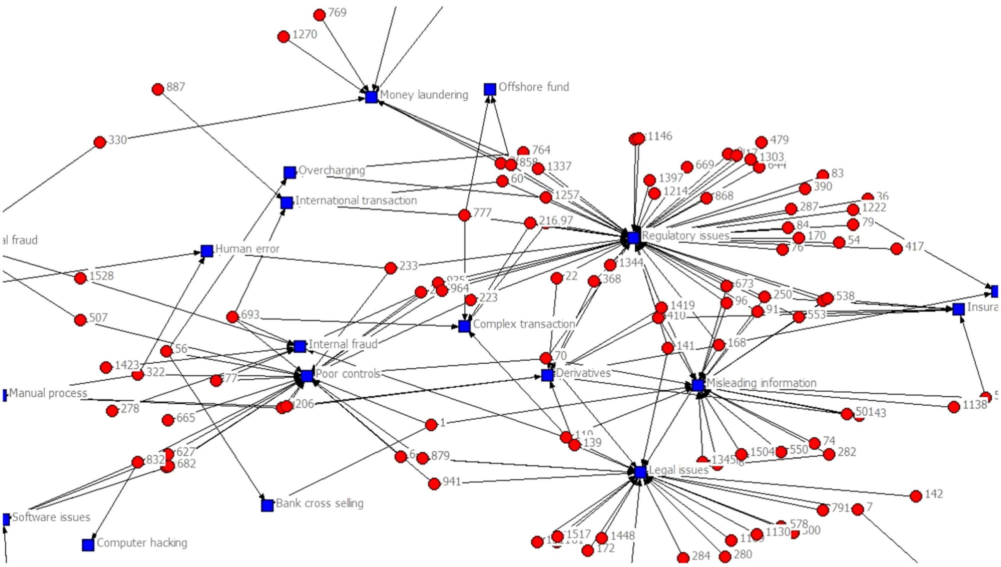

Figure 4. EU major connections.

losses are reasonably determinable, and to be economically attractive, correlations of these extreme operational risk events between the participants should be low. Our analysis shows:

- The EU and US banking systems do have a large number of potential participants.
- The number of banks with extreme operational risk events is relatively small, and the losses are highly skewed, indicating that statistically based pricing may be difficult.

Table 8. Dominant network characteristics for operational risk events 2008–2014.

EU	US
Regulatory issues	Legal issue
Misleading information	Misleading information
Legal issues	Poor controls
Poor controls	Derivatives
Derivatives	Regulatory issues
Insurance	Complex products
Complex transaction	Internal fraud
Money laundering	Complex transaction
Internal fraud	International transaction
International transaction	Money laundering

- The banks with extreme operational risk events do not appear to be serial offenders, i.e., the losses appear to be reasonably spread over the banks that have these losses, and by implication, extreme operational risk events could occur for all banks.
- There are a small number of systemic characteristics or drivers of the extreme operational risk events, but these main drivers occur also as lower level characteristics in other risk events, and the overall number of significant drivers is reasonably large.

These features of extreme operational risk events would suggest that it might be difficult to convince a large number of banks who have not incurred these extreme losses to join a pooled arrangement, and for the pool to be feasible, regulatory compulsion may be required "in the interests of the economy" to achieve stability of the banking system. On the positive side, the lack of serial offenders, and the reasonably large number of significant characteristics would suggest that sufficient diversification within the pool may be achievable, but this is derived from the reasonably large number of drivers of the extreme events and not from international diversification, so country-specific pooled arrangements could be feasible, at least in the United States and European. Pricing of the risks involved would require capping the losses claimable due to the highly skewed distribution of losses and the potential for unexpected losses.

7. Potential Pooled Arrangements

The analysis suggests that for at least the US and EU banks, pooled arrangements could be established domestically, but smaller economies may need to establish pools across several economies simply to have adequate numbers of participants. But even in the United States and European, compulsory participation and capping of losses that could be claimed would be required to make the pool economically attractive. Given the results of Ganegoda & Evans (2013), a charging structure based on each bank's assets would appear reasonable and simple to operate.

8. Conclusion

A pooled arrangement to insure EU and US banks would appear feasible and would be justified in terms of the benefits to shareholders from avoiding severe share price declines when extreme operational risk events are announced and settled, and the advantage to the community of reducing the risk of instability in the banking system.

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Appendix A

Cladistics Trees for US and EU Extreme Operational Risk Event Losses 2008–2914

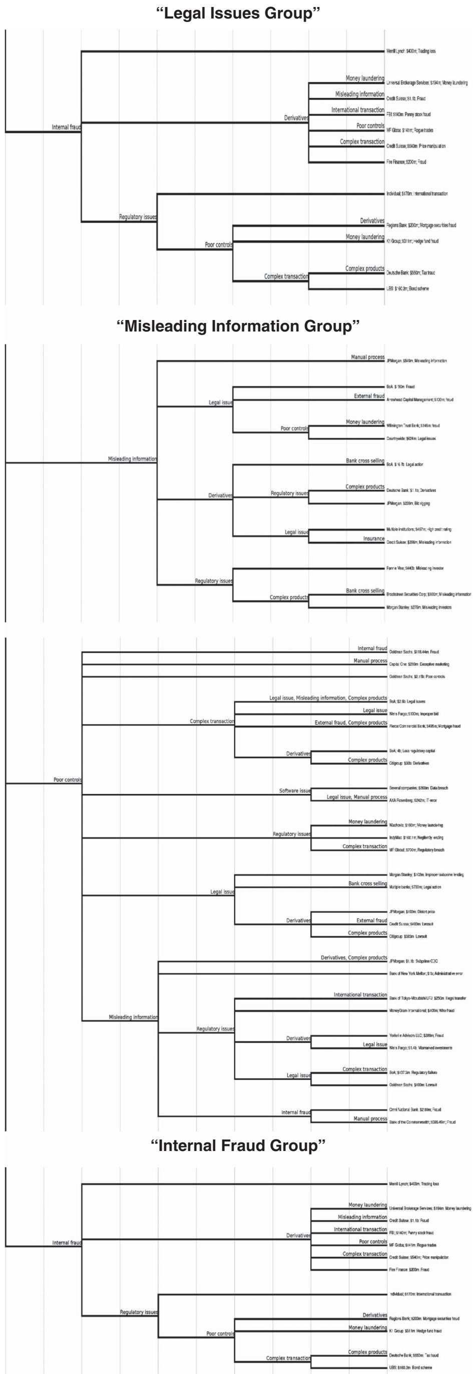

Figure A1. US extreme operational risk losses, major cladistic groups.

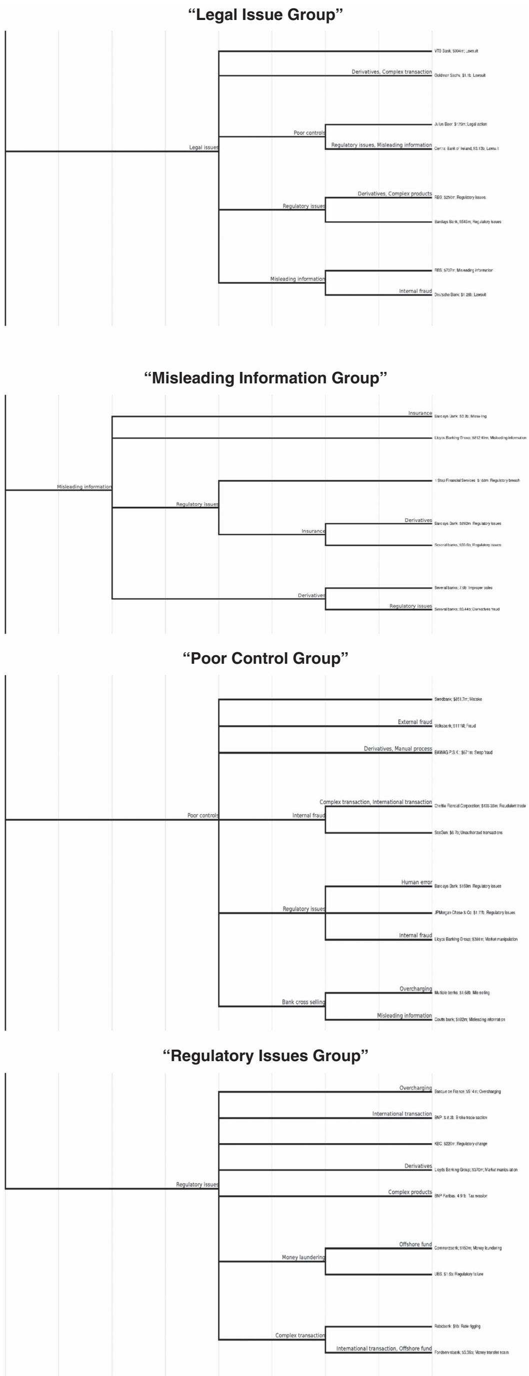

Figure A2. EU extreme operational risk losses, major cladistic groups.